Global Warming and Local Dimming: The Statistical Evidence

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Two effects largely determine global warming: the well-known greenhouse effect and the less well-known solar radiation effect. An increase in concentrations of carbon dioxide and other greenhouse gases contributes to global warming: the greenhouse effect. In addition, small particles, called aerosols, reflect and absorb sunlight in the atmosphere. More pollution causes an increase in aerosols, so that less sunlight reaches the Earth (global dimming). Despite its name, global dimming is primarily a local (or regional) effect. Because of the dimming the Earth becomes cooler: the solar radiation effect. Global warming thus consists of two components: the (global) greenhouse effect and the (local) solar radiation effect, which work in opposite directions. Only the sum of the greenhouse effect and the solar radiation effect is observed, not the two effects separately. Our purpose is to identify the two effects. This is important, because the existence of the solar radiation effect obscures the magnitude of the greenhouse effect. We propose a simple climate model with a small number of parameters. We gather data from a large number of weather stations around the world for the period 1959–2002. We then estimate the parameters using dynamic panel data methods, and quantify the parameter uncertainty. Next, we decompose the estimated temperature change of 0.73°C (averaged over the weather stations) into a greenhouse effect of 1.87°C, a solar radiation effect of −1.09°C, and a small remainder term. Finally, we subject our findings to extensive sensitivity analyses.

KEY WORDS: Aerosols; Decomposition; Dynamic panel data; Greenhouse effect; Solar radiation.

1. INTRODUCTION

The Earth is getting warmer and much or all of this process is generally believed to be caused by humans. There is much uncertainty about global warming. The purpose of this article is to investigate the statistical evidence of global warming, using econometric panel data techniques supplemented by extensive sensitivity analyses.

We distinguish between two effects which together largely determine global warming. First, the concentrations of carbon dioxide (CO_2) and other greenhouse gases have increased. For example, the amount of CO_2 in the atmosphere has increased by about 36% between 1750 and 2005 (Solomon et al. 2007, chap. 2, p. 137). These greenhouse gases act as a blanket, thus contributing to global warming: the greenhouse effect. Because of the long lifetime of CO_2 in the atmosphere, this effect is global.

The second effect, not as well known by the general public, is the solar radiation effect. Pollution consists, in part, of small particles called aerosols which reflect and absorb sunlight in the atmosphere and make clouds more reflective. More aerosols implies that less sunlight reaches the Earth: global dimming (Power 2003; Norris and Wild 2007; Wild 2009). Global dimming varies in time and location. The term global in global dimming is somewhat misleading, because it refers to the sum of diffuse and direct solar radiation (global radiation), and not to a global scale of the phenomenon (Wild 2009, p. 1). In fact, dimming is primarily a local or regional effect, because aerosols have a short lifetime (about one week) in contrast to greenhouse gases which have a lifetime of up to 100 years (Kaufman, Tanré, and Boucher 2002). As a result of the dimming the Earth becomes cooler: the solar radiation effect (Haywood and Boucher 2000; Ramanathan et al. 2001; Kaufman, Tanré, and Boucher 2002; Bellouin et al. 2005). Global warming thus consists of two components: the (global) greenhouse effect and the (local) solar radiation effect, which work in opposite directions.

When we observe an increase in temperature, we observe only the sum of the greenhouse effect and the solar radiation effect, but not the two effects separately. Our purpose is to try and identify the two effects. This is important because policy makers are successful in reducing aerosols (which has a local benefit) but less successful in reducing CO_2 (which has a global, but almost no local benefit). A reduction in aerosols causes cleaner air (good), but also more solar radiation (bad). The solar radiation effect thus obscures the magnitude of the greenhouse effect, and forecasts ignoring the solar radiation effect underestimate the increase in temperature. The size of the solar radiation effect is uncertain (Anderson et al. 2003; Andreae, Jones, and Cox 2005), and hence the solar radiation effect offsets the greenhouse effect by an unknown amount.

Current methods to assess the effect of greenhouse gases in the presence of aerosols typically use global climate models, requiring a large number of parameters whose values are typically obtained by calibration rather than estimation. The reliability of such models is reviewed in Räisänen (2007). The values for the effect of greenhouse gases and aerosols on temperature vary greatly (Anderson et al. 2003; Roe and Baker 2007), thus adding to the controversy about climate change.

Our approach is different. We propose a simple climate model with a small number of parameters. We gather data from a large number of weather stations around the world for the

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Journal of the American Statistical Association
June 2011, Vol. 106, No. 494, Applications and Case Studies
DOI: 10.1198/jasa.2011.ap09508

period 1959–2002. We estimate the parameters using dynamic panel data methods, and quantify the parameter uncertainty. Then we decompose the observed temperature change into a greenhouse and a solar radiation effect.

This article is organized as follows: In Section 2 we discuss the energy balance, which is used to construct our climate model. In Section 3, we describe our data sources, the construction of our dataset, and how we have dealt with a selection problem. The econometric model is presented in Section 4. We report our results and the decomposition in greenhouse and solar radiation effects in Section 5, and we offer extensive sensitivity analyses in Section 6. In Section 7, we conclude.

2. THE ENERGY BALANCE

The Earth and its atmosphere receive energy from the Sun in the form of shortwave radiation, which is partly absorbed, and the energy associated with the absorbed radiation is returned to space as longwave radiation. As long as the amount of incoming solar radiation absorbed by Earth and atmosphere is balanced by Earth and atmosphere releasing the same amount of outgoing radiation, the Earth's temperature will remain the same. A simplified scheme of the energy balance is given in Figure 1, which is based on Trenberth, Fasullo, and Kiehl (2009); see also McGuffie and Henderson-Sellers (2001).

The amount of solar radiation reaching the Earth's atmosphere is about 341 watts per meter squared (Wm^{-2}). Solar radiation has a short wavelength, and hence most of the solar radiation passes through the atmosphere and reaches the surface of the Earth (184 Wm^{-2}). Some of the solar radiation, however, is reflected back into space (79 Wm^{-2}) due to clouds and small particles (aerosols) in the atmosphere, and some is absorbed (78 Wm^{-2}) in the atmosphere where it is transferred to heat energy and longwave radiation. When the Sun's radiation reaches the Earth, part is absorbed (161 Wm^{-2}) and transferred to longwave radiation, and part is reflected back into space as shortwave radiation (23 Wm^{-2}). The Earth releases energy (494 Wm^{-2}), consisting of longwave radiation (396 Wm^{-2}) and latent and sensible heat (98 Wm^{-2}). Most of the emitted longwave radiation is absorbed in the atmosphere by clouds and so-called greenhouse gases. The longwave radiation emitted by the atmosphere goes back into space (239 Wm^{-2}) or is radiated back to Earth (333 Wm^{-2}).

The energy absorbed by the Earth's surface thus consists of two components: shortwave from the Sun (161 Wm^{-2}) and longwave from the atmosphere (333 Wm^{-2}). Without the longwave component the average temperature on Earth would be about −18°C, while in fact it is about 13.5°C. The longwave component exists because of the presence of greenhouse gases (and clouds), which act as a blanket for the longwave radiation coming from the Earth's surface (McGuffie and Henderson-Sellers 2001): the *greenhouse effect*. One of the most important greenhouse gases is carbon dioxide (CO_2). While the natural greenhouse effect is crucial for the climate on Earth, human activities have intensified it. For example, the amount of CO_2 in the atmosphere has increased by about 36% between 1750 and 2005, primarily through the combustion of fossil fuels and tropical deforestation, and by about 15% between 1975 and 2005; see Solomon et al. (2007, chap. 2, p. 137). The Earth becomes warmer (*global warming*) and the anthropogenic greenhouse effect is thought to be primarily responsible for the speed at which this happens (Solomon et al. 2007, chap. 9, p. 665). The greenhouse effect is a global effect, and hence heavy industries and deforestation in one area affect people everywhere.

Increased pollution not only results in a higher concentration of CO_2, but also in more aerosols. An increase in aerosols implies that less sunlight reaches the Earth's surface (*global dimming*), and hence the Earth becomes cooler: the *solar radiation effect*. Global warming thus consists of two components: the greenhouse effect and the solar radiation effect, which work in opposite directions.

We propose a climate model based on the simplified energy balance described above. Our model is inspired by the energy balance models proposed by Budyko (1969), Sellers

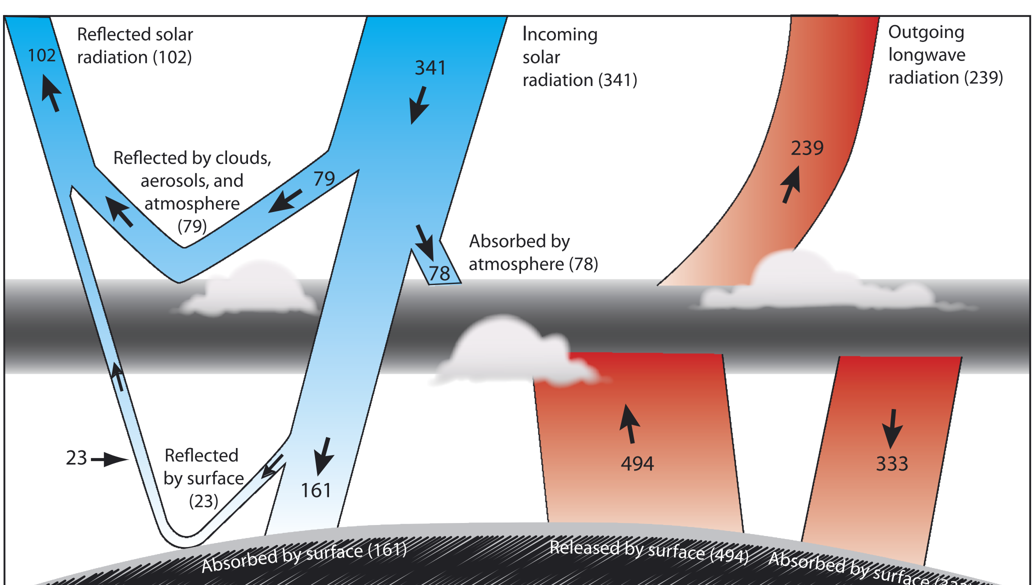


Figure 1. The Earth's annual energy balance (Wm^{-2}) (adapted from Trenberth, Fasullo, and Kiehl 2009). The online version of this figure is in color.

(1969), North, Cahalan, and Coakley (1981), and others; see also Gregory et al. (2002), Andreae, Jones, and Cox (2005), and Schwartz (2007) for recent applications.

If the energy balance at the Earth would hold exactly, then (combining the energy balances at the Earth's surface and the atmosphere)

$$E^{\text{sin}} - E^{\text{lout}} = 0, \tag{1}$$

where $E^{\text{sin}} = (161 + 78)\ \text{Wm}^{-2}$ denotes the incoming solar shortwave radiation which reaches and is absorbed by the Earth or the atmosphere and $E^{\text{lout}} = 239\ \text{Wm}^{-2}$ is the longwave radiation emitted from the atmosphere. In reality, the energy balance will not hold exactly and this imbalance will result in a change in temperature, modeled as

$$\frac{c(\text{TEMP}_{t+\Delta t} - \text{TEMP}_t)}{\Delta t} = E_t^{\text{sin}} - E_t^{\text{lout}}, \tag{2}$$

where c is the so-called heat capacity, linking the energy surplus or deficit to a change in temperature per unit of time (Andreae, Jones, and Cox 2005).

While Equations (1) and (2) refer to the Earth as a whole, we wish to consider weather stations on the Earth's surface. The energy balance (1) then still applies with two modifications. First, the various energy terms will be station specific. Second, weather stations near the equator (latitude zero) receive more sunlight than stations at lower or higher latitudes. Some of this excess radiation will flow from warmer areas to colder areas, resulting in an additional term E^{exch}, representing the net in- or outflow of energy. Thus, if the energy balance would hold exactly in weather station i, then $E_{it}^{\text{sin}} - E_{it}^{\text{lout}} + E_{it}^{\text{exch}} = 0$, but when there is an imbalance, the discrepancy will result again in a change in local temperature TEMP_{it}, modeled for station i at time t as

$$\frac{c(\text{TEMP}_{i,t+\Delta t} - \text{TEMP}_{it})}{\Delta t} = E_{it}^{\text{sin}} - E_{it}^{\text{lout}} + E_{it}^{\text{exch}}. \tag{3}$$

Equation (3) is the starting point for our econometric climate model. The four energy terms will depend on solar radiation, greenhouse gas concentration, and temperature.

3. DATA AND DESCRIPTIVE STATISTICS

We require annual data at the level of weather stations. For each station we collected monthly observations on temperature (TEMP): the average temperature in degrees Celsius (°C) at the surface (source: CRU); solar radiation (RAD): the amount of sunlight (global solar irradiance) that reaches the Earth's surface, measured in watts per meter squared (Wm^{-2}) (source: GEBA); and carbon dioxide (CO_2): concentration of carbon dioxide, measured in parts per million by volume (ppmv) (source: Mauna Loa Observatory). In addition, we need for each station its longitude and latitude. The data are constructed from three sources.

The *Climatic Research Unit (CRU)* maintains a database of monthly climate observations based on a large number of weather stations around the globe (land stations only, Antarctica excluded) over the period January 1901 to December 2002. We use the database labeled CRU TS 2.1 (*http://www.cru.uea.ac.uk*). Information is provided on nine climate variables including TEMP. Some areas of the Earth contain more weather stations than others. In order to obtain regularity of information, the surface of the Earth is defined on a high-density (0.5°) latitude–longitude grid, thus dividing the Earth in 720 × 360 grid cells, each covering an area of about 45 × 45 kilometers. Each grid cell draws potential information from about 100 weather stations, both within and in the neighborhood of the grid cell. The landmass (excluding Antarctica) covers about 26.5% of the Earth. Monthly information is thus provided for each of the nine climate variables in each of 67,420 cells on the landmass. The construction of the database includes checks for inhomogeneities, the use of neighboring stations to fill in gaps, and spatial and temporal interpolation using station data from different datasets (Mitchell and Jones 2005). There exist other sources for TEMP, such as the weather station data from the National Climatic Data Center (NCDC). The CRU dataset is, however, the most extensive, and where the CRU and NCDC data overlap geographically we do not find systematic differences.

The *Global Energy Balance Archive* (*GEBA*) is project A7 of the World Climate Programme—Water (WMO/ICSU). The GEBA database stores monthly means of energy fluxes which have been instrumentally measured at the surface, and is publicly available (*http://www.iac.ethz.ch/groups/schaer/research/rad_and_hydro_cycle_global/geba*). The quality of the energy flux monthly means is controlled. The database provides us with monthly observations on solar radiation over the period 1950–2006, under both cloudy and cloudfree conditions. We only consider the observations from January 1959 to December 2002, because the CO_2 data are not available before 1959 and the CRU data are not available after 2002. Over this 44 year period the GEBA database contains monthly data from 2164 weather stations around the Earth. We delete stations on boats and stations with a quality flag (unreliable). Of the remaining stations there are many where some of the observations are missing. We include only those stations which have at least one complete year of observations. This leaves us with 1337 stations. Figure 2 shows that the weather stations are not spread evenly over the continents, and this could have implications which we discuss and resolve in Section 6. If the solar radiation data on these 1337 stations were complete we would have $44 \times 1337 = 58{,}828$ complete years, while in fact we have only 18,604 complete years. An average weather station has thus only about 14 complete years of solar radiation data. The "holes" can occur at the beginning, the middle, or the end of each time series. For the GEBA weather stations the geographical information on longitude and latitude (and elevation) is also available. See Gilgen and Ohmura (1999) for a detailed description of the GEBA database.

The *Mauna Loa Observatory (MLO)* in Hawaii is one of the baseline observatories of the National Oceanic and Atmospheric Administration. The dataset we are using is the oldest continuous carbon dioxide concentration dataset available, and provides monthly and annual data on CO_2, the concentration of carbon dioxide, measured in parts per million volume, from January 1959 to the present. It is publicly available (*http://www.mlo.noaa.gov/home.html*). Since CO_2 is well mixed in the atmosphere (Solomon et al. 2007, chap. 2, p. 138), we may assume that CO_2 is the same for each weather station and hence we don't require CO_2 data at station level.

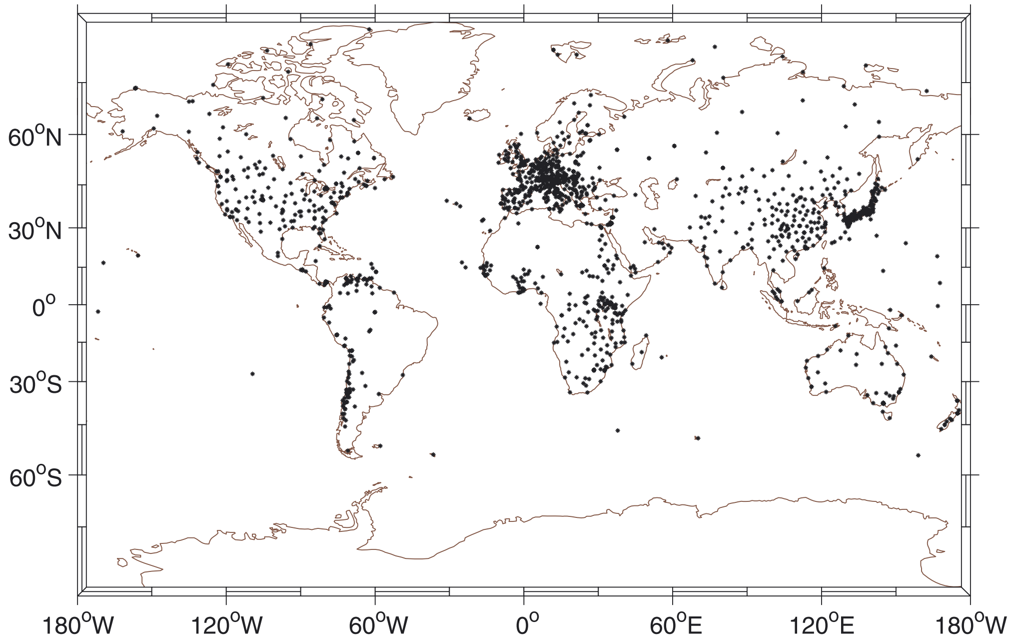


Figure 2. Distribution of weather stations in the GEBA dataset. The online version of this figure is in color.

From these three sources we obtain monthly observations on TEMP (1901–2002); RAD and geographical variables (1950–2006); and CO_2 (1959–present). This gives a period of 44 years (1959–2002) for which all variables are observed. To construct a consistent dataset over the 1959–2002 period we add TEMP to the RAD dataset. Given the location of the weather stations in the RAD dataset, and the division of the Earth into grid cells by CRU, we determine for each RAD station the corresponding grid cell in the CRU division, and thus allocate to each RAD station the appropriate CRU data. We use annual data rather than monthly data in order to avoid the difficult problem of seasonal adjustments. The annual data are obtained by simple averaging of the monthly data, except for the CO_2 series where annual data are provided by the Mauna Loa Observatory. This results in a panel dataset consisting of observations over 1337 weather stations during 44 years.

Monthly observations on TEMP are available, but only about 32% of the monthly observations on RAD is available. When solar radiation is not observed at some weather station during one of the months in a particular year, the corresponding observation is classified as a *missing item observation* (where "missing item" applies to missing information on solar radiation only). As a consequence our dataset is an unbalanced panel with 18,604 (out of a possible 58,828) annual observations without missing items.

Table 1 presents the sample statistics for TEMP, RAD, and CO_2. For temperature we present information both for the complete panel (the panel including the missing item observations) and for the unbalanced panel (the panel without the missing item observations). For solar radiation we can only present information for the unbalanced panel, and for CO_2 we present the sample statistics based on the annual data. The rows labeled "overall" consider all the data (58,828 for TEMP in the complete panel, 18,604 for TEMP and RAD in the unbalanced panel, and 44 for CO_2). The rows labeled "between" consider cross-section averages (1337 stations), and the rows labeled "within" consider time-series averages (44 years for the complete panel and 13.91 years for the unbalanced panel). We see from Table 1 that the sample average of solar radiation in the unbalanced panel is 160.91 Wm^{-2}, ranging from a lowest year average (over weather stations) of 148.77 Wm^{-2} to a highest year average of 183.21 Wm^{-2}, and that the level of CO_2 at the Mauna Loa Observatory increased from 315.98 ppmv in 1959, the first year of the panel, to 373.10 ppmv in 2002, the final year.

The average temperature in the complete panel is 13.4°C, ranging from a year average (over all weather stations) of 12.91°C in the coldest year to 14.14°C in the warmest year, and ranging from a station average (over all years) of −19.96°C in the coldest weather station to 29.75°C in the warmest weather station. In the unbalanced panel some of the temperature averages are substantially lower, up to almost 1.5°C. This suggests that the missing observations may not be missing completely at random (MCAR), and hence that a (potentially serious) sample selection problem may exist, at least in terms of the *level* of temperature. We are, however, primarily interested in a decomposition of temperature *changes* (in the time

Table 1. Sample statistics for TEMP, RAD, and CO_2

Variable		Mean	Std.	Min	Max
TEMP	overall	13.40	8.90	−22.04	31.23
complete panel	between		8.89	−19.96	29.75
	within		0.34	12.91	14.14
TEMP	overall	11.93	8.43	−22.04	30.36
unbalanced panel	between		8.90	−20.74	29.77
	within		0.61	10.66	13.21
RAD	overall	160.91	42.46	52.00	324.00
unbalanced panel	between		44.68	55.46	316.00
	within		9.09	148.77	183.21
CO_2		340.88	17.55	315.98	373.10

Table 2. Sample statistics for time differences in temperature

Variable		Mean	Std.	Min	Max
ΔTEMP	overall	0.0142	0.7311	−4.9250	5.1583
complete panel	between		0.0162	−0.0583	0.0944
	within		0.2580	−0.5140	0.5726
ΔTEMP	overall	0.0136	0.7600	−4.9250	5.1583
unbalanced panel	between		0.2802	−3.6167	1.5500
	within		0.3451	−0.6495	0.8305

period 1959 to 2002). To investigate whether there is a selection problem due to missing item observations in terms of temperature changes we present in Table 2 the complete and unbalanced panel for time differences in temperature. Because we take first differences there are now only 43 years and hence $43 \times 13{,}337 = 57{,}491$ observations for TEMP in the complete panel, and 15,388 in the unbalanced panel. The average annual temperature change in the complete panel is 0.0142°C, only slightly higher than the average annual temperature change in the unbalanced panel (0.0136°C). The overall difference between the two panels is thus only 0.0006°C per year, and this difference is statistically not significant (p-value = 0.85). For individual weather stations the time averages in the complete and unbalanced panels sometimes differ substantially. This is because for some weather stations only a few years are without missing items, implying that extreme weather conditions may have a large impact for these stations. This is also reflected by the corresponding between standard deviations: only 0.0162 in the complete panel, but 0.2802 in the unbalanced panel.

Regarding the year averages over weather stations (the two rows labeled "within"), we see that the difference between the complete and unbalanced panel is small, and this is further illustrated in Figure 3, where we present the annual temperature changes (averaged over all weather stations) in both the complete and the unbalanced panel for 1960–2002. We tested the null hypothesis that the mean temperature changes for each of the years from 1960 to 2002 in both panels are equal, but could not reject the null hypothesis (p-value = 1.00). Hence we conclude that, when dealing with temperature changes, we may treat the missing observations as MCAR.

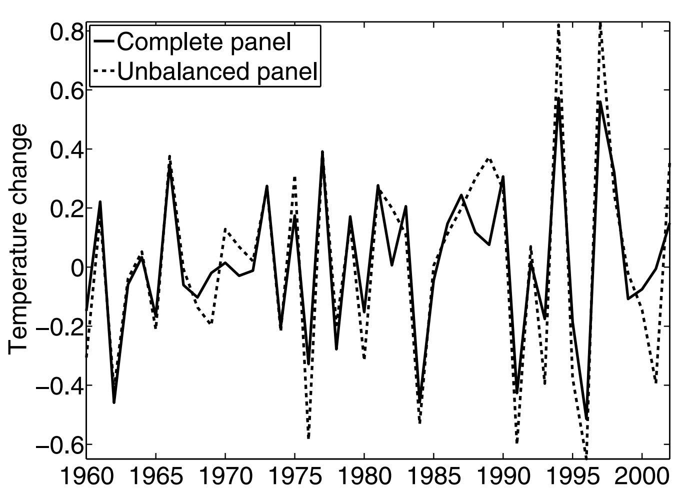


Figure 3. Average temperature change, 1960–2002.

The average temperature change over the weather stations in our panel is not necessarily the same as the global average temperature change. However, a comparison of our average temperature change with the global average temperature change based on the CRU data for land air temperature or the CRU data for combined land and marine temperature, indicates that the decomposition of our average temperature change (into the greenhouse and radiation effects) will also be informative for these global temperature changes.

4. THE ECONOMETRIC MODEL

4.1 Specification of the Energy Flows

Our econometric model is based on Equation (3) in annual terms ($\Delta t = 1$ year):

$$c(\mathrm{TEMP}_{i,t+1} - \mathrm{TEMP}_{it}) = E_{it}^{\mathrm{sin}} - E_{it}^{\mathrm{lout}} + E_{it}^{\mathrm{exch}}, \qquad (4)$$

where the energy terms represent annual measurements. Let us specify the three energy flows, following Budyko (1969) with minor modifications; see also Sellers (1969), North (1975), and North, Cahalan, and Coakley (1981).

We allow for both a global and a local solar radiation effect, and we therefore specify

$$E_{it}^{\mathrm{sin}} = a_0 + a_1\overline{\mathrm{RAD}}_t + a_2(\mathrm{RAD}_{it} - \overline{\mathrm{RAD}}_t),$$

where $\overline{\mathrm{RAD}}_t$ denotes the average solar radiation at year t and $(\mathrm{RAD}_{it} - \overline{\mathrm{RAD}}_t)$ the local solar radiation in excess of average solar radiation. We have $a_1 \geq a_2 \geq 0$, because an increase in either $\overline{\mathrm{RAD}}_t$ or RAD_{it} leads to an increase in E_{it}^{sin}. The global effect is captured by $a_1\overline{\mathrm{RAD}}_t$, while $a_2(\mathrm{RAD}_{it} - \overline{\mathrm{RAD}}_t)$ captures the local effect. There is no global effect if $a_1 = a_2$, and no local effect if $a_2 = 0$. We shall assume that changes in solar radiation are caused by changes in anthropogenic aerosol emissions: more aerosols lead to a decrease in solar radiation (Power 2003; Norris and Wild 2007). Our analysis does not, however, depend on this assumption, and changes in solar radiation can also be influenced by other factors, such as variations in the solar constant.

The outgoing longwave energy is an increasing (nonlinear) function of temperature, and also depends on the concentration of greenhouse gases in the atmosphere, which we represent by the concentration of CO_2. Assuming a constant vertical lapse rate (cf. North 1975), the atmosphere's temperature depends linearly on the Earth's surface temperature. Since greenhouse gases are assumed to be evenly spread around the globe, we model their effect to be constant over weather stations. Based on these considerations, we approximate the outgoing longwave energy by the following linear function:

$$E_{it}^{\mathrm{lout}} = b_0 + b_1\overline{\mathrm{TEMP}}_t + b_2(\mathrm{TEMP}_{it} - \overline{\mathrm{TEMP}}_t) - b_3\log\bigl(\mathrm{CO}_{2t}\bigr),$$

where $\overline{\mathrm{TEMP}}_t$ denotes the average temperature at year t, $b_1 \geq b_2 \geq 0$, and $b_3 \geq 0$. Again, we allow for both a local and a global effect. Finally, the exchange energy term is modeled as

$$E_{it}^{\mathrm{exch}} = c_0 - c_1(\mathrm{TEMP}_{it} - \overline{\mathrm{TEMP}}_t)$$

with $c_1 \geq 0$. Thus, if the local temperature in weather station i is larger than the average temperature, then there is an outflow of energy from station i; if the local temperature is lower than the average, there is an inflow. The parametrizations for E_{it}^{lout} and E_{it}^{exch} are based on Budyko (1969), North (1975), and North, Cahalan, and Coakley (1981). The dependence on CO_2 via a log-transformation is based on Solomon et al. (2007, chap. 2, p. 140).

With these specifications substituted into Equation (4) we obtain, after suitable parameter transformations,

$$\text{TEMP}_{i,t+1} = \beta_1 \text{TEMP}_{it} + \beta_2 \text{RAD}_{it} + \lambda_t, \tag{5}$$

$$\lambda_t = \gamma_0 + \gamma_1 \overline{\text{TEMP}}_t + \gamma_2 \overline{\text{RAD}}_t + \gamma_3 \log(\text{CO}_{2t}). \tag{6}$$

We can estimate the β's and the γ's, but not the underlying structural parameters, unless we make further assumptions, for example, about the heat capacity c.

4.2 Steady State

The system gives rise to a steady state temperature, both at a global and local level, obtained by setting $\text{TEMP}_{i,t+1} = \text{TEMP}_{it}$ for all weather stations i at a given year t. The global average steady state temperature at year t will be denoted by $\overline{\text{TEMP}}_t^e$ and the local steady state temperature in weather station i at year t by TEMP_{it}^e. The steady state temperatures are then given by

$$\overline{\text{TEMP}}_t^e = \frac{\gamma_0 + (\beta_2 + \gamma_2)\overline{\text{RAD}}_t + \gamma_3 \log(\text{CO}_{2t})}{1 - \beta_1 - \gamma_1} \tag{7}$$

and

$$\text{TEMP}_{it}^e = \overline{\text{TEMP}}_t^e + \frac{\beta_2}{1 - \beta_1}(\text{RAD}_{it} - \overline{\text{RAD}}_t). \tag{8}$$

The global average steady state temperature is thus determined by the global average solar radiation level and the level of the greenhouse gases (represented by CO_2). The local steady state temperature may deviate from the global average steady state temperature via a deviating local solar radiation level.

Using the steady state temperatures (7) and (8) we can decompose a change in local or global steady state temperature into a solar radiation effect and a greenhouse effect. For example, a change in global steady state temperature is given by

$$\Delta \overline{\text{TEMP}}_t^e = \frac{\beta_2 + \gamma_2}{1 - \beta_1 - \gamma_1} \Delta \overline{\text{RAD}}_t + \frac{\gamma_3}{1 - \beta_1 - \gamma_1} \Delta \log(\text{CO}_{2t}), \tag{9}$$

where the first term represents the change in the steady state temperature due to a change in solar radiation (e.g., caused by dimming), while the second term represents the change in the steady state temperature due to a change in CO_2. In a similar way, we can calculate decompositions at a local level or at a partially aggregated level (such as a continent).

Again using (7) and (8), we can rewrite Equations (5) and (6) as

$$\text{TEMP}_{i,t+1} - \text{TEMP}_{it} = (1 - \beta_1)(\text{TEMP}_{it}^e - \text{TEMP}_{it}) - \gamma_1(\overline{\text{TEMP}}_t^e - \overline{\text{TEMP}}_t),$$

which reveals that the system is mean reverting (as long as $\beta_1 \leq 1$, $\gamma_1 \leq 0$, and the steady state temperatures are taken as the means), where $-\gamma_1$ quantifies the speed of mean reversion for deviations from the global steady state temperature, and $1 - \beta_1$ quantifies the speed at the local level.

4.3 Uncertainty

In a world without uncertainty, the development of temperature over time and weather stations is assumed to be determined by Equations (5) and (6), where $i = 1, \ldots, N$ indexes the weather station ($N = 1337$) and $t = 1, \ldots, T$ the year ($T = 44$). There is, however, considerable uncertainty about nonlinearities, omitted variables, and many other issues. Uncertainty is introduced through three channels. We have a station-specific effect α_i, which captures any effects specific for weather station i, not changing over time (at least, not changing over the sample period); a time-specific effect η_t, which captures those station-independent time effects not captured by $\overline{\text{TEMP}}_t$, $\overline{\text{RAD}}_t$, and $\log(\text{CO}_{2t})$; and a station-specific and time-dependent idiosyncratic effect u_{it}. Introducing these three error terms results in the following econometric specification for weather station i at year t:

$$\text{TEMP}_{i,t+1} = \beta_1 \text{TEMP}_{it} + \beta_2 \text{RAD}_{it} + \alpha_i + \lambda_t + u_{i,t+1}, \tag{10}$$

$$\lambda_t = \gamma_0 + \gamma_1 \overline{\text{TEMP}}_t + \gamma_2 \overline{\text{RAD}}_t + \gamma_3 \log(\text{CO}_{2t}) + \eta_t. \tag{11}$$

Once the parameters in the two equations have been estimated, the steady state temperatures and the decompositions discussed in the previous subsection can be calculated straightforwardly.

In order to estimate the parameters in (10) and (11) we need to impose distributional assumptions. In our specification there is cross-sectional dependence via the time effects λ_t. To deal with this dependence, we consider (10) conditional on λ_t. Given λ_t, we assume independence over the weather stations. The λ_t will then capture cross-sectional correlation. We shall make distributional assumptions similar to those proposed in Arellano and Bond (1991), and Blundell and Bond (1998), and this allows us to estimate (in a first round) the β-parameters in (10) and also the time effects λ_t, using standard panel data estimation techniques. Next, given the estimated time effects, we use (11) together with the usual linear regression assumptions to estimate the γ-parameters in a second round by ordinary least squares.

We now describe the distributional assumptions that we impose on (10), in addition to assuming independence over weather stations, conditional on the time effects. For each weather station i and time period t in our dataset we shall assume

$$\text{E}[\alpha_i + u_{it}] = 0, \tag{A1}$$

$$\text{E}[u_{i,t-s}(\alpha_i + u_{it})] = 0 \qquad (s \geq 1), \tag{A2}$$

$$\text{E}[\Delta \text{RAD}_{i,t-s} \Delta u_{it}] = 0 \qquad (s \geq 1), \tag{A3}$$

$$\text{E}[\text{TEMP}_{i,t-s} \Delta u_{it}] = 0 \qquad (s \geq 2), \tag{A4}$$

$$\text{E}[\Delta \text{TEMP}_{i,t-s}^e (\alpha_i + u_{it})] = 0 \qquad (s \geq 1). \tag{A5}$$

Assumptions (A1) and (A2) are standard zero mean and zero correlation assumptions for the station-specific and idiosyncratic error terms. Assumptions (A3) and (A4) are standard zero correlation assumptions between independent or lagged dependent variables and error terms. Assumption (A5) concerns the change in steady state temperature, and states that future error terms do not deviate systematically with this change. Moreover, we assume for some $\tau \leq 1$, possibly far back in the past and independent of i,

$$\mathrm{TEMP}_{i,\tau} = \mathrm{TEMP}^e_{i,\tau}. \tag{A6}$$

This assumption can be seen as an initial condition, stating that the system was in a steady state at some point in the past.

4.4 Correlation

Even though (conditional on the time effects) the idiosyncratic errors u_{it} are assumed to be independent over weather stations and have to satisfy (A2), the complete error term in (10)–(11) equals $\alpha_i + \eta_t + u_{i,t+1}$. This implies that cross-sectional and time correlation is built into the model, and we illustrate this fact under additional mean-independence assumptions [which imply Assumption (A1)]. We first consider correlation over time, and we write $\mathrm{cov}(\mathrm{TEMP}_{i,t+1}, \mathrm{TEMP}_{it}) = C_1 + C_2$, where

$$C_1 = \mathrm{cov}[\mathrm{E}(\mathrm{TEMP}_{i,t+1}|\mathcal{I}_{it}), \mathrm{E}(\mathrm{TEMP}_{it}|\mathcal{I}_{it})],$$
$$C_2 = \mathrm{E}[\mathrm{cov}(\mathrm{TEMP}_{i,t+1}, \mathrm{TEMP}_{it}|\mathcal{I}_{it})]$$

represent the covariance captured by the systematic part, and the covariance due to the error terms (conditional upon $\mathcal{I}_{it}$), respectively, and

$$\mathcal{I}_{it} = \{\mathrm{TEMP}_{i,t-1}, \mathrm{RAD}_{it}, \mathrm{RAD}_{i,t-1}, \mathrm{CO2}_t, \mathrm{CO2}_{t-1}, \overline{\mathrm{TEMP}}_{t-1}, \overline{\mathrm{RAD}}_t, \overline{\mathrm{RAD}}_{t-1}\}$$

denotes the conditioning set. We are interested in C_2 and we shall show in Section 5.1 that C_2 is relatively small. The additional mean-independence assumption is $\mathrm{E}(\alpha_i + \eta_t + u_{i,t+1}|\mathcal{I}_{it}) = 0$, which implies that the average conditional expectation equals the unconditional expectation. Given our distributional assumptions,

$$\begin{aligned} C_2 = {} & \beta_1 \,\mathrm{var}(\alpha_i + u_{it}) + \gamma_1 \,\mathrm{cov}(\overline{\alpha} + \overline{u}_t, \alpha_i + u_{it}) \\ & + (\beta_1 + \gamma_1)\,\mathrm{var}(\eta_{t-1}) + \mathrm{var}(\alpha_i) \\ & + \mathrm{cov}(\alpha_i, u_{i,t+1}). \end{aligned} \tag{12}$$

This shows that the error structure generates time correlation in two ways, due to the autoregressive nature of the model ('state dependence') captured by the first three terms (if $\beta_1 \neq 0$ or $\gamma_1 \neq 0$), and due to the correlation of the individual effect with itself and with the idiosyncratic error term (unobserved heterogeneity) captured by the final two terms.

Next, we consider spatial correlation. We decompose $\mathrm{cov}(\mathrm{TEMP}_{i,t+1}, \mathrm{TEMP}_{j,t+1})$ in the same way as before, but with a different conditioning set, namely

$$\widetilde{\mathcal{I}}_{ijt} = \{\mathrm{TEMP}_{it}, \mathrm{RAD}_{it}, \mathrm{TEMP}_{jt}, \mathrm{RAD}_{jt}, \overline{\mathrm{TEMP}}_t, \overline{\mathrm{RAD}}_t, \mathrm{CO2}_t\}.$$

The mean-independence assumption now reads $\mathrm{E}(\alpha_i + \eta_t + u_{i,t+1}|\widetilde{\mathcal{I}}_t) = 0$, and, using our distributional assumptions, the second term in the covariance decomposition is equal to $\mathrm{var}(\eta_t)$. Thus, the error term in the time effect captures the error-term-specific cross-sectional correlation.

4.5 Moment Restrictions With Missing Observations

Some solar radiation observations are missing and this may cause a selection problem. We now describe how the distributional assumptions (A1)–(A6) can be manipulated to construct moment restrictions such that the parameters in (10) can be estimated by the Generalized Method of Moments (GMM) in the presence of missing observations.

We introduce selection variables r_{it}, such that $r_{it} = 0$ if observation (i, t) on solar radiation is missing, and $r_{it} = 1$ if the observation is present. Conditional on the time effect, we combine the distributional assumptions (A1)–(A6) with the assumption that the missing observations are MCAR, except possibly for the level. By this we mean that under the assumption that the selection variables are independent of the random variables appearing in (A1)–(A6), the moment restrictions are valid in terms of the parameters appearing in (10), except possibly for the level. Since the level will be captured by the time effects λ_t, our assumption implies that we may not be able to estimate the level of the time effects consistently, but we will be able to estimate, for example, $\lambda_t - \lambda_1$ consistently.

We use the following moment restrictions in estimating the parameters of (10):

$$\mathrm{E}\sum_{t=2}^{T}[r_{i,t-1}(\alpha_i + u_{it})] = 0, \tag{M1}$$

$$\mathrm{E}[r_{i,t-1}r_{i,t-2}\Delta u_{it}] = 0 \qquad (t = 3, \ldots, T), \tag{M2}$$

$$\mathrm{E}\sum_{t=3}^{T}[r_{i,t-1}r_{i,t-2}\Delta\mathrm{RAD}_{i,t-1}\Delta u_{it}] = 0, \tag{M3}$$

$$\mathrm{E}[r_{i,t-1}r_{i,t-2}\mathrm{TEMP}_{i,t-s}\Delta u_{it}] = 0 \quad [t = 3, \ldots, T; s = 2, \ldots, \min(t-1, 4)], \tag{M4}$$

$$\mathrm{E}[r_{i,t-1}(\alpha_i + u_{it})\Delta\mathrm{TEMP}_{i,t-1}] = 0 \quad (t = 3, \ldots, T). \tag{M5}$$

Restrictions (M1) and (M2) are derived from (A1) and the MCAR assumption, where (M2) is obtained by taking time differences of (A1). Restrictions (M3) and (M4) are derived from (A3) and (A4), respectively, together with the MCAR assumption. Restriction (M5) follows from taking time differences of (10) (until reaching $t = \tau$), combined with (A2), (A3), the initial condition (A6), and the MCAR assumption. The restrictions (M1)–(M4) are based on the moment conditions in Arellano and Bond (1991); the additional restriction (M5) is based on Blundell and Bond (1998).

The first round provides consistent estimates of $\lambda_t - \lambda_1$ $(t = 2, \ldots, T-1)$, and we use these estimates in Equation (11). We calculate the global averages of both temperature and solar radiation, using the differences in the unbalanced panel in the following way. Let $\overline{\mathrm{TEMP}}_1$ be the global average temperature in the first year of the complete panel (the panel including the missing observations), and let $\overline{\mathrm{RAD}}_1$ be the global average solar radiation in the first year of the unbalanced panel (the panel without the missing observations). Then, $\overline{\mathrm{TEMP}}_t$ is calculated as

$$\overline{\mathrm{TEMP}}_t = \overline{\mathrm{TEMP}}_{t-1} + \frac{1}{\sum_{i=1}^N r_{it}r_{i,t-1}} \sum_{i=1}^N r_{it}r_{i,t-1}\Delta\mathrm{TEMP}_{it} \tag{13}$$

for $t = 2, \ldots, T$. $\overline{\mathrm{RAD}}_t$ is calculated similarly.

When estimating (11) we impose the usual linear regression assumptions, and we assume that applying least squares yields unbiased estimates, except again for the level. This implies that the constant term may be biased. When calculating the standard errors of the linear regression coefficients, we ignore the first-round inaccuracy, because the number of observations in the first round (N weather stations) is much larger than the number of observations in the second round ($T - 1$ years).

5. EMPIRICAL RESULTS

We now present the empirical results. In Section 5.1 we discuss the estimation results. In Section 5.2 we investigate the 1991 eruption of Mount Pinatubo to test the performance of our model. In Sections 5.3 and 5.4 we present the decomposition of the temperature change into a greenhouse and a solar radiation effect, both in terms of observed and steady state temperatures. We also consider this decomposition at regional levels (continents).

5.1 Parameter Estimates

The estimation results for our model, based on Equations (10) and (11), are presented in Table 3. The first two columns give the estimates and standard errors of the β's in Equation (10), while the next three columns contain the estimates and standard errors of the γ's in Equation (11). All estimates have the expected signs and are statistically significantly different from zero (at the 5% level). The panel-data based estimates of Equation (10) are far more accurate than the time-series based estimates of Equation (11), and this supports our approach to ignore the first-round inaccuracy in the second round. In the subsequent subsections we shall use these parameter estimates to characterize our climate model.

For a dynamic model such as our econometric model, it is standard practice to use the Arellano–Bond estimator, that is, to apply GMM to the moment restrictions (M1)–(M4); see Arellano and Bond (1991). This estimator performs poorly, however, when the autoregressive coefficient β_1 or the variance ratio $\mathrm{var}(\alpha_i)/\mathrm{var}(u_{it})$ is large (Blundell and Bond 1998). Including moment restriction (M5) may then yield better results. In our case the estimate of the autoregressive coefficient is $\hat{\beta}_1 = 0.91$ and the estimate of the variance ratio is 0.98. Both are large, thus motivating our choice to use all moment restrictions (M1)–(M5).

In terms of the implied correlation structure as described in Section 4.4, we estimate that the temporal correlation, calculated from (12), is 0.017 with 0.011 due to state dependence and 0.006 to unobserved heterogeneity. Since the total temporal correlation is 0.996, the error terms contribute only a small part; most is captured by the systematic part of the model. The estimate of the final term in (12), $\mathrm{cov}(\alpha_i, u_{i,t+1})$, is very close to zero, implying that, given the assumptions in Section 4.4, the autocorrelation in the idiosyncratic error terms u_{it} is also estimated to be zero [using (A2)]. The cross-sectional correlation, given by $\mathrm{var}(\eta_t)/\mathrm{var}(\mathrm{TEMP}_{i,t+1})$, is estimated to be 0.002, and the estimate of the total cross-sectional correlation is 0.16. Again, the contribution of the error terms is small.

Table 3. Parameter estimates and standard errors

TEMP_{it} (β_1)	RAD_{it} (β_2)	$\overline{\mathrm{TEMP}}_t$ (γ_1)	$\overline{\mathrm{RAD}}_t$ (γ_2)	$\log \mathrm{CO}_{2t}$ (γ_3)
0.9063	0.0087	−0.8235	0.0614	10.6955
(0.0046)	(0.0008)	(0.1839)	(0.0219)	(2.3958)

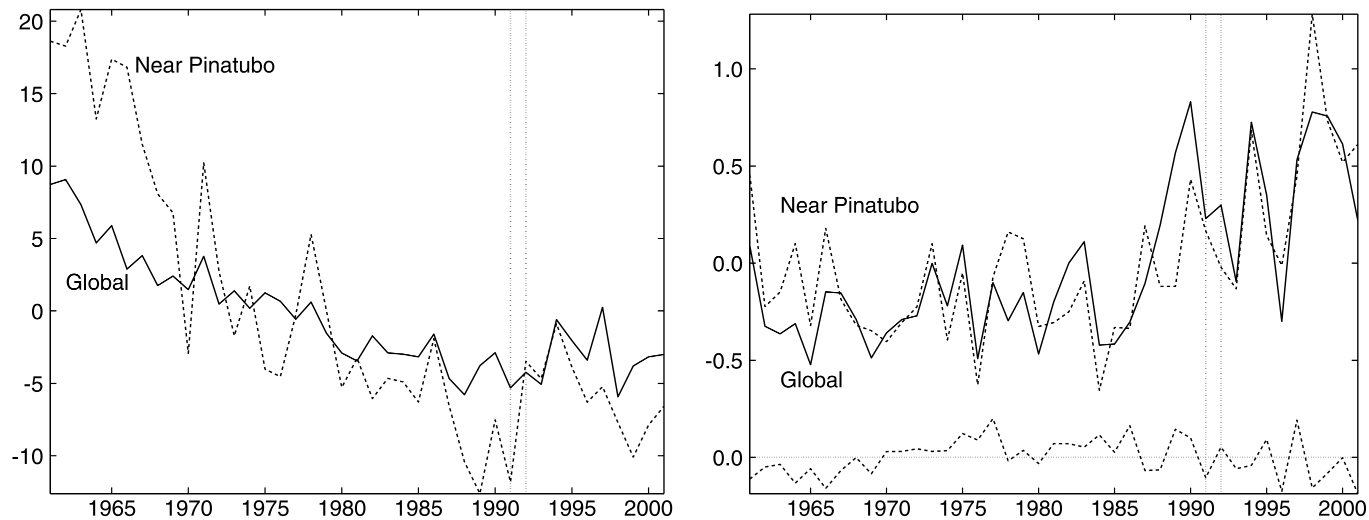
Using the estimated β's and γ's we can investigate whether dimming is a local or a global effect or both. If $H_0: a_1 = a_2$ holds then dimming is only a local effect. In terms of our reduced-form parameters we need to test $H_0: \gamma_2 = 0$. Since $\hat{\gamma}_2$ is significantly different from zero, we reject H_0 and conclude that there is evidence for a global dimming effect. On the other hand, if $H_0: a_2 = 0$ holds then dimming is *only* global. Here we need to test $H_0: \beta_2 = 0$ and this is also rejected. Hence, we find both a local and a global dimming effect, but since a_1 is much larger than a_2, the local effect is much more important than the global effect.

The specification (10)–(11) is linear in the independent variables. This linear specification should be seen as a linear approximation to a nonlinear structure. To test the validity of the linear approximation, we performed a number of specification tests. In particular, we calculated the in-sample predictions according to the specification (10)–(11), and compared these to three in-sample predictions, where in each case one of the linear terms in (11) was replaced by a fully flexible specification in this variable, estimated nonparametrically using Robinson's (1988) semiparametric regression approach. Only in case of CO_2 do we find some statistically significant differences between our linear specification and the alternative partial nonparametric regression in-sample predictions, indicating that, at least in-sample, the linear specification performs well.

5.2 Mount Pinatubo

How confident can we be that our results are driven by and identified in the data, and not just an artifact of model choice? A natural environment for studying this question is to consider a shock in one of the explanatory variables, say solar radiation. If the model is correctly specified, then this should lead to a shock in the prediction of the dependent variable (temperature), but not to a shock in the residuals. A large volcanic eruption provides the ideal environment, and the June 1991 eruption of Mount Pinatubo on the island of Luzon in the Philippines was the largest eruption in our data period, in fact, the largest disturbance of the stratosphere since the eruption of Krakatau in 1883. An estimated 30 teragrams (megatonnes) of aerosols were released into the atmosphere.

Figure 4 summarizes our analysis. In panel (a) we present the solar radiation time series for the 100 stations closest to Mount Pinatubo ("Near Pinatubo") and compare this series with the solar radiation time series for all stations in our dataset ("Global"). Both series are normalized so that their average over the period is zero. The two vertical lines indicate the years 1991 (the year of the eruption) and 1992. The "Pinatubo effect" is clearly visible: the global average in 1991 is 5.33 Wm^{-2} lower than the average over 1959–1990, and near the Pinatubo even 12.95 Wm^{-2} lower. This effect is largest near Mount Pinatubo, since the eruption lasted until August, with episodic eruptions in September. But there is also a global effect due to the fast dispersion of the aerosols across the globe: the aerosol



(a) Solar radiation (b) Temperature and residuals

Figure 4. Analysis of the Mount Pinatubo eruption.

cloud moved westward and circled the globe in approximately 22 days (McCormick, Thomason, and Trepte 1995).

Our model predicts that there should be a temperature shock in 1992, and this negative effect on temperature is visible from panel (b), not just in 1992 but also in 1993. We should be a little careful in our conclusions, because both solar radiation and temperature are volatile (especially the graphs based on only 100 stations).

The key graph is at the bottom of panel (b) where we plot the (scaled) residuals, averaged over the stations close to Mount Pinatubo. There is no sign of any anomaly in the residuals. It seems justified, therefore, to have confidence that our results are driven by and identified in the data.

5.3 Greenhouse and Solar Radiation Effects

The purpose of this article is to try and decompose the observed (in-sample) total change in temperature into a change that can be attributed to a change in the concentration of greenhouse gases, and a change caused by a change in the solar radiation reaching the surface. Our econometric model enables us to do this, and Figure 5 illustrates the resulting decomposition.

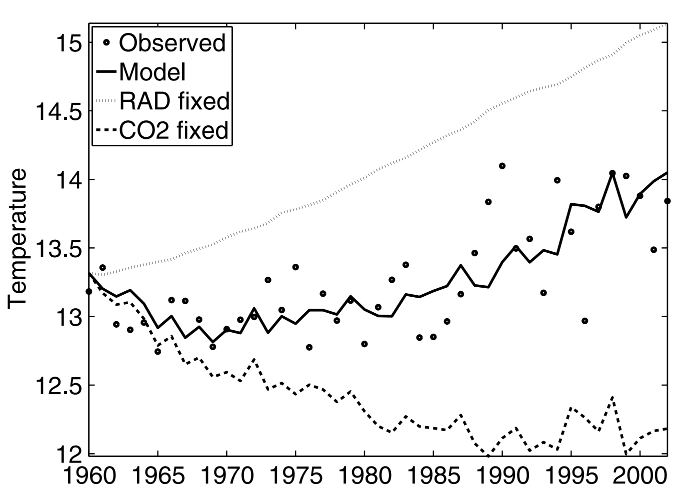


Figure 5. Decomposition of temperature change, 1960–2002.

The dots represent the observed global average temperature, calculated using Equation (13), and setting $\overline{\mathrm{TEMP}}_1$ equal to the average temperature in the first year of the complete panel. The solid curve gives the expected global average temperature according to our model, conditional on the observed development of carbon dioxide and solar radiation. We set the level of this curve such that its time average equals the time average of the observed temperature series. The in-sample change in average temperature equals 0.66°C (1960–2002), while the model predicts the slightly higher temperature change of 0.73°C. The solid curve follows the actual series closely, and hence our model is able to reproduce the pattern of in-sample temperature changes well.

Two further temperature series are presented in Figure 5, and these represent the decomposition. The lower curve shows the expected temperature if carbon dioxide is assumed to remain at its 1959 level (the start of our dataset). The upper curve shows the expected temperature if solar radiation is assumed to remain at the level of 1959. The difference between the lower curve and the solid curve can be interpreted as the greenhouse effect for the period 1959–2002, while the difference between the upper curve and the solid curve can be interpreted as the solar radiation effect. The figure shows that, without the increase in greenhouse gases, the expected global average temperature would have been 1.87°C lower (with standard error 0.32): the greenhouse effect. Also, if global average solar radiation is unchanged from its initial level, then the expected global average temperature would have been 1.09°C higher (standard error 0.31): the solar radiation effect. The predicted temperature change of 0.73°C thus decomposes as $0.73 = 1.87 - 1.09 - 0.05$, where 0.05 is a remainder term due to the fact that we are not in a steady state. We conclude that the solar radiation effect is important, masking 58% of the increase due to the greenhouse effect.

Let us compare these findings with the literature. Such a comparison should be interpreted with some care, because existing studies use different time periods than our study, and some focus on specific regions. Furthermore, our solar radiation effect includes factors other than aerosols that influence the amount of incoming solar radiation. Taking these caveats into account, we find that the existing findings broadly agree with ours. Tett et al. (2002) report a greenhouse effect of 0.9°C per century. Stott et al. (2006) find that 0.7–1.3°C of warming is due to greenhouse gases, and that 0.33–0.49°C of cooling is due to aerosols. Allen et al. (2006) find that the twentieth century greenhouse effect is in the range of 0.3–1.2°C, with a cooling of 0.7°C due to aerosols. Our results imply a more important greenhouse effect.

Regarding the solar radiation masking effect, Crutzen and Ramanathan (2003) report a masking effect of 45% from 1850 to the present. Applying their reasoning to the results in Anderson et al. (2003) yields values in the range 37%–56% for the same time period. Similarly, applying their reasoning to Bellouin et al. (2005) and Myhre (2009) yields values of 70% and 11%, respectively. For 1930–2002, Ramanathan et al. (2005) find that aerosols may have masked as much as 50% of the surface warming due to the global increase in greenhouse gases. Our findings in terms of the relative importance of the solar radiation effect are in line with this literature.

Actual changes may be different from steady state changes to which they will converge. Therefore we investigate the steady state effects next.

5.4 Steady State Effects

We decompose the steady state temperature change in the period 1960–2002 into a solar radiation and a greenhouse effect, both globally and regionally, at the level of continents. At the global level, the change in average steady state temperature equals 0.92°C (standard error 0.18). The global average steady state temperature would have been 1.90°C (0.35) lower without the increase in CO_2, while the average steady state temperature would have been 0.98°C (0.31) higher if global average solar radiation would still be at its initial level. Notice that the decomposition in steady state contains no remainder term: $0.92 = 1.90 - 0.98$. Our results imply that the global mean-reverting coefficient $-\gamma_1$ equals 0.82 (0.18). The mean-reverting speed at the global level is therefore high, and convergence to the global steady state temperature is fast.

At the regional (continent) level, the changes in steady state temperature may differ, due to local dimming. These regional effects, calculated using (8), are illustrated in Figure 6, where we show the decomposition for four continents: Africa, Asia, Europe, and North America. The graphs are similar to Figure 5, except that the curves now show steady state temperatures. In North America the average steady state temperature would have

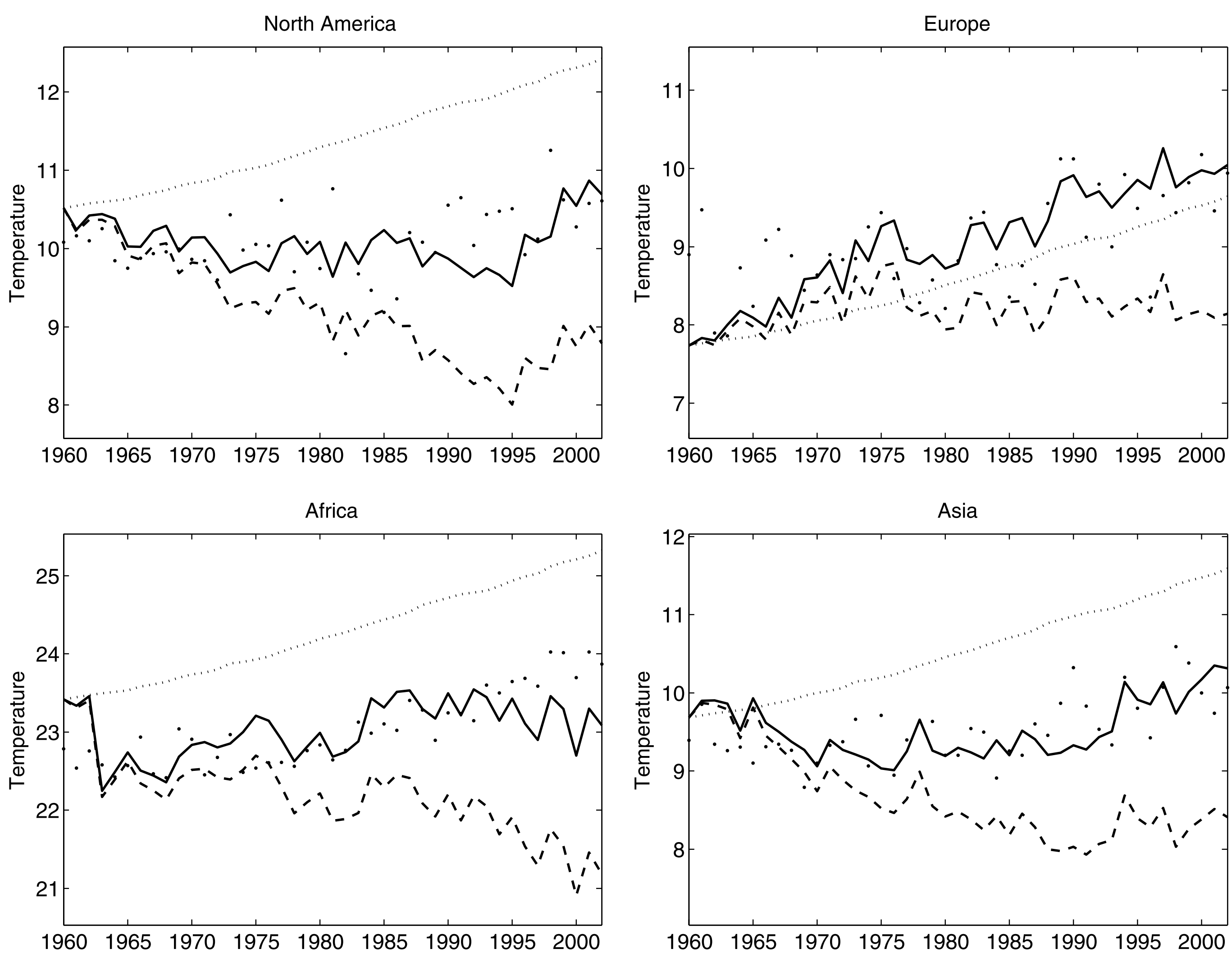


Figure 6. Decomposition of temperature change by continent, 1960–2002.

been 1.73°C higher in the case where solar radiation would still be at the 1960 level. In Asia the temperature would be 1.73°C higher, and in Africa even 2.23°C. The uncertainty of these effect estimates are similar to those in Figure 5, since they are based on the same parameter estimates. One would perhaps expect that the solar radiation effect in Asia becomes larger in comparison with North America in the 1990s, due to the expansion of the Asian economies and the associated increase in sulfur emissions. However, external data on sulfur emissions reveal that Chinese sulfur emissions leveled off after 1989, and this is consistent with Figure 6. These results demonstrate that the local solar radiation effect may be different from the global effect, and also much more important than the greenhouse effect, masking even more than 100% of the temperature increase due to the greenhouse effect. The local mean-reverting coefficient $1 - \beta_1$ equals 0.094 (standard error 0.005). The local mean-reverting speed is thus much lower than the global mean-reverting speed, implying that convergence at local levels can be slow.

6. SENSITIVITY ANALYSIS

Our benchmark model is based on a large number of assumptions, in particular about the climate model, about the statistical model, and about the data. Any or all of these assumptions may be incorrect. In this section we ask whether small deviations from our assumptions will cause large or small changes in our conclusions. In the former case the conclusions are apparently sensitive to a particular assumption; in the latter case they are not. Obviously we prefer that our conclusions are not sensitive, but this is something that needs to be investigated, especially in the context of climate change where there is much uncertainty about the process. We organize our sensitivity analyses in three groups: climate model issues, statistical model issues, and data issues. In our sensitivity analysis we focus on Figure 5, that is, we ask the following question: How sensitive to our assumptions is the decomposition of the total temperature change into a change due to greenhouse gases represented by CO_2 (the greenhouse effect) and a change due to dimming (the solar radiation effect)? Table 4 summarizes our results.

6.1 Climate Model Issues

We consider two ways to change the climate model. The first is to make the solar radiation effect latitude dependent. The second is to consider a static model.

In our benchmark model we made the assumption that the solar radiation effect is the same for each weather station. One might argue however that the solar radiation effect depends on the latitude, due to a latitude-specific albedo effect. We investigate two methods to allow for this dependency.

In the first method (model 2a), we divide the Earth into six latitude zones of equal size. We let $\mathrm{RAD}^l_{it} = \mathrm{RAD}_{it}$ if station i is in zone l, and 0 otherwise ($l = 1, \dots, 6$), and we replace $\beta_2 \mathrm{RAD}_{it}$ in (10) by $\sum_{l=1}^{6} \beta_{2l} \mathrm{RAD}^l_{it}$. We find that all radiation coefficients are positive, and that they are lower for zones further away from the equator. The implications for the decomposition are that, compared to our benchmark results, the solar radiation effect decreases and the greenhouse effect increases.

In the second method (model 2b), we let the radiation coefficient be a linear function of the distance to the equator, that is, $\beta_{2,i} = a_0 + a_1 |\mathrm{LAT}_i/90|$, where a_1 is allowed to be different per hemisphere. We find that both the solar radiation effect and the greenhouse effect increase. Hence, if we assume that the solar radiation effect is latitude-dependent, then the magnitude of the solar radiation effect does not change systematically, but may become smaller or larger than the benchmark, depending on the way the dependence on latitude is modeled. But since in both models the greenhouse effect increases, we find that the solar radiation effect only masks 39% or 53% of the increase due to the greenhouse effect.

Our climate model is based on the idea that a surplus or a deficit in the energy balance causes a change in temperature. This results in our dynamic specification (10)–(11). Alternatively, one could set up a climate model by linking the temperature to the energy level. Such an approach leads to a static panel data model, for example, our model (10)–(11), but then with $\beta_1 = \gamma_1 = 0$ and with TEMP_{it} as dependent variable instead of $\mathrm{TEMP}_{i,t+1}$. We estimate this static model (model 3) imposing moment restrictions analogous to the benchmark model. We find lower solar radiation and greenhouse effects, where

Table 4. Sensitivity analysis: solar radiation and greenhouse effects

	Method		Solar radiation	Greenhouse
1	Benchmark		−1.09 (0.31)	1.87 (0.32)
Climate model issues				
2a	Albedo		−0.92 (0.34)	2.34 (0.41)
2b			−1.20 (0.29)	2.24 (0.28)
3	Static		−0.78 (0.15)	1.59 (0.17)
Statistical model issues				
4a	Lags:	Two lags	−1.05 (0.31)	1.84 (0.32)
4b		Four lags	−1.08 (0.31)	1.88 (0.32)
5	Arellano–Bond		−0.78 (0.29)	1.73 (0.30)
6	One round		−0.07 (0.03)	1.08 (0.03)
Data issues				
7	Definition of $\overline{\mathrm{TEMP}}$		−1.16 (0.25)	1.78 (0.24)
8	Spatial Independence		−1.07 (0.32)	1.95 (0.33)
9	Weights		−1.43 (0.28)	1.71 (0.25)
10a	1/2 most complete stations		−0.88 (0.30)	1.73 (0.30)
10b	2/3 most complete stations		−1.10 (0.31)	1.86 (0.31)

the solar radiation effect becomes, relatively speaking, somewhat less important (49%). Without a dynamic autoregressive part, the individual station-specific effect becomes much more important than in the benchmark model, capturing 0.918 (instead of 0.012) of the total temporal autocorrelation of 0.996. In this case the individual effects also capture some of the station-specific trends over time, leading to lower solar radiation and greenhouse effects. Overall, we conclude that the decomposition of the total temperature change into a change due to greenhouse gases represented by CO_2 (the greenhouse effect) and a change due to dimming (the solar radiation effect) is not very sensitive to our assumptions.

6.2 Statistical Model Issues

We investigate the sensitivity of the decomposition with respect to three deviations in the statistical model. First, for restriction (M4), we have chosen a maximum of three lags of TEMP to be used as instruments. We consider as alternatives two lags (model 4a) and four lags (model 4b). This has only a small effect on the decomposition results. Second, we use the moment restrictions (M1)–(M4) in our benchmark model, based on Arellano and Bond (1991), extended with the moment restriction (M5) as in Blundell and Bond (1998). Model 5 is obtained by estimating the model using only (M1)–(M4). Even though the underlying parameter estimates change significantly, the results in terms of the decomposition are close to those of the benchmark model.

Third, we consider a restricted version of our benchmark model, where we do not estimate the model in two rounds, but in one round (model 6). We use Equations (10)–(11), but set the time-specific parameter to zero, thus ignoring possible cross-sectional correlations. We estimate the model using the moment conditions (M1)–(M5). In terms of the decomposition, we find a substantial decrease in the greenhouse effect, while the solar radiation effect becomes quite small (although still statistically significantly different from zero). The high accuracy of the estimates is due to the single-round estimation, based solely on the large number of weather stations. Without the time-specific intercepts, the imposed time structure does not seem to allow for sufficient flexibility, resulting in findings quite different from the other specifications.

6.3 Data Issues

Finally, we consider four data issues. In the benchmark model we have calculated the mean temperatures $\overline{\text{TEMP}}_t$ and the mean solar radiation levels $\overline{\text{RAD}}_t$ using differences in the unbalanced panel, in order to avoid potential sample selection problems caused by missing observations. But these averages can be calculated in various ways. In model 7 we take, as an alternative, the following temperature and solar radiation means in the second round:

$$\overline{\text{TEMP}}_t = \frac{1}{N}\sum_{i=1}^{N}\text{TEMP}_{it}, \qquad \overline{\text{RAD}}_t = \frac{\sum_{i=1}^{N} r_{i,t+1}\text{RAD}_{it}}{\sum_{i=1}^{N} r_{i,t+1}}.$$

Thus we take the average in year t in the complete panel to calculate $\overline{\text{TEMP}}_t$, and the average in year t in the unbalanced panel to calculate $\overline{\text{RAD}}_t$. This changes the levels, in particular the level of temperature. The corresponding decomposition effects (which are changes) are close to the benchmark. Hence, the alternative way of calculating the means affects the levels, but not the changes in a statistically significant way, and this is in line with our assumption that the unbalanced sample is representative for the complete panel in terms of (temperature) changes.

When we calculate the spatial correlation using the model-based idiosyncratic error terms $u_{i,t+1}$ and $u_{j,t+1}$, we find that this correlation is negligible for weather stations further apart, in line with our assumptions. Only for weather stations close to each other, we find spatial correlation, which disappears rapidly with increasing distance. This spatial correlation between weather stations that are close is due to the construction of the dataset, where weather stations in the same grid cell share the same temperature data. To see whether our decomposition results are sensitive to this spatial correlation in the idiosyncratic error terms of nearby weather stations, we consider a subsample of our sample, by drawing randomly one weather station from each temperature grid cell. This reduces the number of weather stations by 153, while the number of observations becomes 16,949 instead of 18,395 (model 8). The resulting changes in the solar radiation and greenhouse effects are minor.

In the benchmark model we assume a random sample, conditional upon the time effects. However, the weather stations are not evenly spread over the continents. For example, the ratio of South American weather stations to its landmass is too low, while for Europe it is too high. To deal with this uneven spread of weather stations over the continents, we estimate a weighted version (model 9) of the benchmark model, with weights w_i ($i = 1, \ldots, N$) defined as the proportional size divided by the proportional number of observations of the continent where station i is located. We adapt the definition of $\overline{\text{TEMP}}_t$ and $\overline{\text{RAD}}_t$ accordingly. In this model, the solar radiation effect is larger (and estimated more accurately), while the greenhouse effect is slightly smaller (and also estimated more accurately). However, we find no statistically significant differences between the decomposition effects of the weighted and unweighed versions.

For most weather stations we do not have full records on solar radiation during the whole sample period. For some weather stations we observe solar radiation only during some years, while for other weather stations we observe solar radiation during most years. Our assumption is that this unbalanced structure of our panel is not causing a selection effect. A recommended way to check this, is to compare the estimation results with a more balanced subpanel, including only the weather stations with (more) complete records; see Verbeek and Nijman (1992). We consider the more balanced subpanel, containing one-half of the weather stations with the most complete solar radiation records (model 10a). Both the solar radiation effect and the greenhouse effect become smaller. As a result, the solar radiation effect now masks 51% (instead of 58% in the benchmark model) of the increase due to the greenhouse effect. If we chose $2/3$ instead of $1/2$, then the results in Table 4 (model 10b) are almost identical to our benchmark results. The missing observations do therefore have an effect on our results, as one would expect, but this effect is small.

7. CONCLUSIONS

In this article we propose a climate model based on the Earth's energy balance. We then modify this climate model to obtain an econometric model, and we estimate its parameters using dynamic panel data methods. Our data consist of solar radiation, temperature, and carbon dioxide concentrations from 1337 weather stations around the world for the period 1959–2002.

During the 43 years 1960–2002 temperature increased by an estimated 0.73°C, which we decompose as $0.73 = 1.87 - 1.09 - 0.05$, namely a greenhouse effect of 1.87°C (standard error 0.32), a solar radiation effect of 1.09°C (0.31), and a remainder term of 0.05. Hence, if aerosols and solar radiation would have remained at the 1959 level, then the expected global average temperature would have been 1.09°C higher. The solar radiation effect is therefore important, masking 58% of the increase due to the greenhouse effect. Ignoring dimming thus causes a serious underestimation of the greenhouse effect.

Our approach has several strengths and several weaknesses. The weak points are that some important climate processes (e.g., carbon storage in the ocean) are not modeled; that only land stations and no sea stations are considered; and finally that data availability limits our time horizon. Some would also criticize our frequentist (as opposed to Bayesian) approach. While modeling environmental data based on Bayesian hierarchical models has become popular and such models provide a clear framework for dealing with the various aspects of the climate system and with data issues, we have not chosen for this approach because of the much more restrictive distributional assumptions that have to be made on the sources of uncertainty, and on the variable that contains the missings.

The strong points are that our model is simple enough to allow estimation rather than calibration of the reduced-form parameters and their uncertainties, that the reduced-form parameters are all that is needed for our analysis, and that analysis at all levels of aggregation is possible. Our main result is contained in Figure 5, where we present the decomposition in greenhouse and solar radiation effects. An important aspect of the article is the sensitivity analysis. We present not only Figure 5, but we also ask how the figure would change if we make small adjustments to our underlying assumptions. Climate models are often criticized for not being robust. Extensive sensitivity analysis demonstrates that our conclusions are relatively robust against small changes in a variety of assumptions.

[Received September 2009. Revised January 2011.]

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Comment

T. STORELVMO and T. LEIRVIK

1. INTRODUCTION

In their pioneering study applying statistical and econometric analysis to a climate dataset, Magnus, Melenberg, and Muris (2011), hereafter MMM, present a decomposition of the temperature trend over the last four decades of the 20th century into a solar radiation component and a greenhouse gas component. While it is well known that atmospheric greenhouse gas (GHG) concentrations are increasing steadily in response to anthropogenic fossil fuel burning and thereby heating the planet, the general public is less aware of a corresponding downward trend in solar radiation reaching the surface. The latter is very likely due to higher concentrations of particles (so-called aerosols) in the atmosphere, also as a result of anthropogenic fossil fuel and biomass burning. Aerosols can both (1) directly increase the amount of solar radiation scattered back to space and (2) brighten clouds such that they become more reflective to solar radiation. Hence the observed reduction in solar radiation reaching the surface during the second half of the 20th century, which is sometimes referred to as "global dimming" but will be termed "the aerosol effect" for the remainder of this discussion.

2. THE DRIVERS OF CLIMATE CHANGE: GREENHOUSE GASES VERSUS AEROSOLS

The aerosol effect acts to cool the climate and partly compensate for the warming due to increasing GHG concentrations, and is currently one of the most uncertain aspects of projections of future climate. This is largely because of the complicated and poorly understood processes involved in the emissions and atmospheric lifetimes of aerosols, and their interactions with clouds and radiation while airborne. In Storelvmo et al. (2009), four different methods for calculating the aerosol brightening of clouds in global climate models (GCM) were compared, and yielded coolings that ranged from negligible to comparable in magnitude to the warming due to increasing greenhouse gases. This wide uncertainty range for the aerosol effect is problematic for the following reason: The GCMs that were employed to simulate future climate in the last report from the Intergovernmental Panel for Climate Change (IPCC) (23 in total; Randall et al. 2007) report vastly different so-called Equilibrium Climate Sensitivities (ECSs). The ECS is defined as the change in mean surface air temperature in response to a doubling of atmospheric CO_2. The ECS ranged from 2.1°C to 4.4°C for the 23 models that participated in this Climate Model Intercomparison Project (*http://www-pcmdi.llnl.gov/ipcc/about_ipcc.php*). Surprisingly, despite the wide range of ECSs among the models, they were all able to reasonably reproduce the observed temperature record for the 20th century. However, in a recent article by Kiehl (2007) an explanation for this puzzle was offered; they found that there was a strong negative correlation between the magnitude of the aerosol effect and the ECS for a subset of the 23 models discussed above. This can be understood as follows: A GCM with anomalously high climate sensitivity may yield an exaggerated warming trend in response to increasing GHGs, but can currently compensate for this by choosing an aerosol effect from the upper end of the uncertainty range (corresponding to a relatively strong cooling that masks much of the warming due to GHGs). Similarly, a GCM with anomalously low climate sensitivity can currently choose a negligible aerosol effect. The ECS is therefore largely unconstrained by the observed temperature record of the past, with the result that future climate cannot be predicted with any confidence (global mean surface air temperatures are projected to rise by anything from 1°C to 6°C by year 2100, according to the 4th assessment report from IPCC, hereafter IPCC AR4).

3. COMPARING THE STATISTICS OF OBSERVATIONAL VERSUS MODELING DATASETS

In this context, the interdisciplinary approach taken by MMM is timely and an important contribution. By estimating the parameters of a relatively simple climate model, they are able to make quantitative statements about what fraction of the warming due to increasing GHGs was likely masked by an aerosol effect. This is referred to as a radiation effect in their study, however the only plausible explanation for the observed trend in solar radiation reaching the surface is the increase of atmospheric aerosol concentrations over the examined time period (Wild, Ohmura, and Makowski 2007). This study opens up for the exciting possibility of constraining the aerosol effect in GCMs used to project future climate. However, there are several potential cavities in such an approach, some of which are: (1) Observations of the climate variables relevant for the simplified climate model in MMM are taken from unevenly distributed weather stations, which generally tend to undersample sparsely populated and remote regions with harsh climates; (2) Radiation data is missing for certain time periods and weather stations, complicating the comparison to models further; and (3) The typical resolution of a GCM is currently approximately 2.5×2.5 degrees. In MMM radiation data from individual GEBA weather stations were assigned temperatures from the CRU data set, given on a 0.5×0.5 degrees grid. In other words, for each GCM data point, there will 25 observational data points. The latter two issues are illustrated in Figure 1.

All of the above may result in differences between GCMs and the data analyzed by MMM that are related to data quality rather than actual climate. As an illustration, we have randomly selected one of the GCMs that were used to simulate

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Journal of the American Statistical Association
June 2011, Vol. 106, No. 494, Applications and Case Studies
DOI: 10.1198/jasa.2011.ap11284

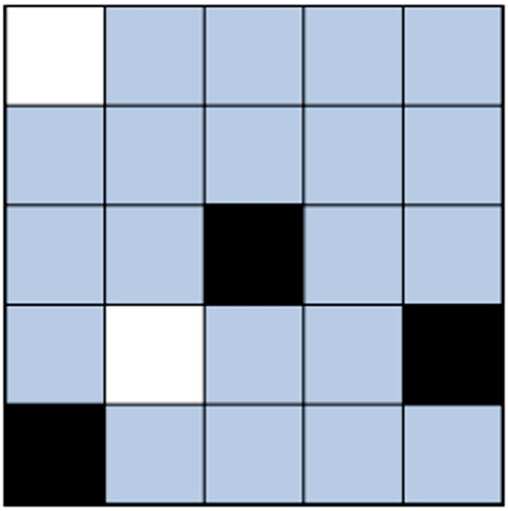

Figure 1. Illustration of one GCM grid box covering 2.5 degrees in the latitude and longitude directions, which corresponds to a maximum of 25 data values from the observational grid. However, as indicated by the black boxes, data is missing in some of the observational grid boxes not containing any weather stations. Furthermore, some observational grid boxes have temperature (TEMP) data but are missing radiation (RAD) data for parts of the time series, as illustrated by the white boxes. The online version of this figure is in color.

future climate for IPCC AR4, and analyzed GCM data from the same time period as considered in MMM (i.e., 44 years, from January 1959 to December 2002). The spatial resolution of this specific GCM is 2.8×2.8 degrees. We have selected only GCM grid boxes that have a minimum of 20% land, and excluded Antarctica, as in MMM. The threshold of 20% is arbitrary, but sensitivity tests revealed little sensitivity to choice of land threshold. The statistics obtained for the variables RAD (downward solar radiation at the surface in Wm^{-2}) and TEMP (surface air temperature in °C), are displayed in Tables 1 and 2. For comparison, we have also included the observational data from Tables 1 and 2 in MMM (for the case of a complete panel for TEMP).

As evident from Table 1, the mean temperature from the GCM is significantly lower (by 4.57°C) than the observational mean. This is not surprising, considering that the observations are undersampling colder regions (see Figure 2 in MMM). The sensitivity of the temperature statistics to the actual weather stations sampled is also illustrated by the difference between the complete and unbalanced panels in MMM. For the same reason, the minimum temperature from the GCM is much lower (by 11.36°C) than the corresponding observational value, while the maximum temperature is almost identical. Because the GCM samples a wider range of temperatures, the location variance is larger in the GCM dataset. However, the year-to-year variability (given by the annual standard deviation) is much smaller in the GCM.

RAD is somewhat larger in the GCM than in the observational dataset. In this case it is less obvious that unevenly distributed observations are causing the difference, but observational data points are clustered at Northern Hemisphere midlatitudes, less dense in the Tropics and very sparse at high latitudes. Another plausible explanation for the discrepancy between the GCM and observations could be poorly represented clouds and aerosols in the GCM. The variance in the GCM dataset is higher, as expected from the wider range of locations sampled.

Table 2 shows the statistics for the time differences in temperature from the GCM and the observations (taken from Table 2 in MMM). The overall mean temperature trend in the GCM is about 1/3 of that observed. Again, because of the unevenly distributed observations differences are expected. However, Arctic regions, that have been observed and projected to warm at a faster rate than the rest of the Globe, are not well represented in the observations. Hence, the discrepancy between the simulated and observed temperature trend is not easily explained by uneven observational sampling. Another alarming difference is that while MMM finds a strong negative trend in RAD over the time period considered [Figure 4(a) in MMM], and concludes that this effect has likely masked 58% of the warming due to greenhouse gases, the GCM simulates no trend in RAD at all (slope coefficient: -0.012, $R^2 = 0.049$) over the same time period. In other words, this particular GCM simulates no masking effect, in strong contrast to the finding in MMM. However,

Table 1. Annual mean sample statistics for TEMP and RAD. The label *overall* refers to a statistic of the entire dataset spanning both time and space, while the between and within labels refer to cross-sectional (averaged over time) and time series (averaged over locations) statistics of the dataset, respectively. The OBS label refers to the observational dataset used in MMM, while the GCM label refers to data generated by a Global Climate Model simulating climate over the time period 1959–2002

Variable		Mean	Std.	Min	Max
TEMP OBS	overall	13.40	8.90	−22.04	31.23
	between	13.40	8.89	−19.96	29.75
	within	13.40	0.34	12.91	14.14
TEMP GCM	overall	8.83	13.79	−33.4	31.22
	between	8.83	13.77	−25.0	30.53
	within	8.83	0.21	8.43	9.29
RAD OBS	overall	160.9	42.46	52.00	324.00
	between	160.9	44.68	55.46	316.00
	within	160.9	9.09	148.77	183.21
RAD GCM	overall	176.3	58.8	53.7	303.0
	between	176.3	58.5	65.6	300.2
	within	176.3	0.61	174.5	177.6

Table 2. Sample statistics for time differences in temperature, that is, the annual mean temperature change from one year to the next. See Table 1 for explanations of labels

Variable		Mean	Std.	Min	Max
ΔTEMP OBS	overall	0.0142	0.731	−4.925	5.158
	between	0.0142	0.016	−0.058	0.094
	within	0.0142	0.258	−0.514	0.573
ΔTEMP GCM	overall	0.0046	1.040	−7.829	7.377
	between	0.0046	0.037	−0.165	0.173
	within	0.0046	0.144	−0.298	0.237

it should be kept in mind that these results are from a single GCM, which may well be an outlier.

4. OUTLOOK

To determine whether GCMs in general are systematically simulating a much weaker aerosol masking effect than the one reported in MMM, further study involving new results from numerous GCMs is required. A fifth report from IPCC is currently underway (due in 2014), and model results from a new CMIP are becoming available. An interesting extension to MMM and the present discussion would be to do equivalent analyses of all models contributing to the CMIP, to determine whether simulated relationships between the aerosol and greenhouse effect are comparable to the one found in MMM. Ultimately, this may aid the climate modeling community in their efforts to determine the true climate sensitivity. Certainly, such a study would have to be interdisciplinary in nature, bringing experts from the statistics and econometrics community and the field of climate science together in an effort to solve a problem that has been identified as one of the major scientific puzzles of our time (Kerr 2005).

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Rejoinder

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We thank the editors for inviting this discussion, and Trude Storelvmo and Thomas Leirvik (henceforth SL) for their kind remarks and thoughtful comments. Our empirical analysis, like almost all statistical analyses, can be criticized from four angles: choice of model, estimation technique, suitability of the data, and applicability. We shall briefly touch on each of these, although SL focus on the applicability aspect. Their principal concern is whether our approach, in particular the decomposition of the temperature change into a greenhouse effect and a solar radiation effect (called the "aerosol effect" by SL), can be used in calibrating global climate models (GCMs). SL raise and illustrate a number of issues that might complicate such an application. This is an important concern and it was not discussed in our article. So we welcome the opportunity to discuss it now. We first consider the tension between model complexity and statistical feasibility, and clarify the difference between a GCM and our model, then we turn to the applicability issue, and finally we mention some other potential limitations.

A GCM is a detailed model of the climate system. It allows for interaction and feedback effects, and typically depends on many (unknown) parameters. A GCM is complex—too complex to allow a "proper" statistical analysis. There are two reasons why this is so. First, given the available data, such as observations on surface temperature, the parameters of a GCM are typically not identifiable: simulating the climate with different combinations of parameter values might result in the same temperature series, so that the observed temperature data does not

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Journal of the American Statistical Association
June 2011, Vol. 106, No. 494, Applications and Case Studies
DOI: 10.1198/jasa.2011.ap11319

suffice to distinguish between different parameter values. Second, even if the parameters of a GCM would be identifiable (e.g., if many additional data would be available), estimation of the parameters would still be difficult or even impossible due to the highly complex (nonlinear) nature of the GCMs. Therefore, GCMs cannot be estimated in the usual way; instead, they are calibrated. Such calibrations are successful in the sense that GCM-based simulations of, for example, the *past* global mean surface temperature are in good agreement with the observed global mean surface temperature (Kiehl 2007). However, when simulating *future* climate, different GCMs might result in quite different climate characteristics. Hence, there is a need for better, more detailed, calibrations of GCMs, and, as discussed by SL, a proper quantification of the solar radiation effect is important in achieving this.

In contrast, our model is relatively simple, perhaps too simple. Our approach is data driven. Given the available data and taking the data characteristics into account, we construct a simple statistical (reduced-form) climate model whose parameters are identifiable and can be estimated and tested using standard statistical and econometric techniques. We require that the model is sufficiently simple that a "proper" statistical analysis can still be carried out. But at the same time the model should be rich enough so that important climate characteristics, including the solar radiation effect, can be estimated (in a statistically credible manner) and the accuracy of these estimates can be quantified.

The question raised by SL is how to use our estimated solar radiation effect to help constrain the solar radiation effect in GCMs. They mention three potential problems in our approach: (1) weather stations are unevenly distributed, (2) radiation data are sometimes missing, and (3) the typical GCM grid is 2.5×2.5 degrees, while our grid is finer, namely 0.5×0.5 degrees. Our model employs weather stations as observational units. These weather stations are unevenly spread across the globe with some areas (like Europe) overrepresented, and other (sparsely populated) areas underrepresented. On the other hand, using a relatively large grid, GCMs produce climate outcomes that are evenly spread across the globe. Comparing our weather-station-based sample averages with averages calculated from evenly spaced grids only makes sense after appropriate corrections. To link a GCM to our approach we might select the GCM-based grids in which a sufficient number of weather stations (available in our dataset) is located. Suppose we are given some variables of interest (such as temperature change and the solar radiation effect), and wish to use these to compare the GCM with our model. In case of the GCM the values of these variables can be simulated for each of the grids and for each time period. In case of our model we can determine for each of the selected grids and for each time period aggregate (or representative) values for these variables, using the weather stations located in the grid. This aggregation also solves the missing radiation data problem. In this way we obtain comparable values of the variables of interest for the selected grids and time periods both for the GCM and our model, which will help us in selecting or calibrating suitable GCM parameter values. Alternatively, we might complement our model with assumptions allowing us to determine the values of the variables of interest also for the grids without a sufficient number of weather stations. If we follow this approach, our model will be able to generate an aggregate or "representative" outcome (in terms of the variables of interest) for each of the grids of a GCM, which will help us in selecting or calibrating suitable GCM parameter values.

Finally, let us mention three problems not raised by SL, but nevertheless of importance.

- *Omitted ocean.* Our analysis is based on land observations only. Hence, our decomposition should be interpreted as a land-based decomposition, unless we are willing to make additional assumptions on the relation between sea and land. In addition, although our model allows for some time-invariant, nonsystematic transfer of energy into the ocean, we do not model this transfer explicitly. This potentially biases the results.
- *Measurement of the level of greenhouse gases.* There are two limitations in the measurement of the level of greenhouses gases. First, we proxy this level by considering only carbon dioxide. This is valid if the change in total greenhouse gas forcings is proportional to the change in forcing from carbon dioxide, which may be a reasonable approximation. Second, the observational record for greenhouse gases that we use is short. Ideally, we would have a time series going back a few hundred years so that we could identify long-run relationships between carbon dioxide and temperature.
- *Uncertainty.* Our approach has the advantage of quantifying the uncertainty of the parameter estimates, that is, we do not only report our estimates, but also the degree of certainty with which we can say something about the effects. Our standard errors are quite large, which means that there is considerable uncertainty. Where does this uncertainty come from? Are the variables measured imprecisely? Is the model too simple so that much of the climate variability is not captured? Or is the climate system perhaps chaotic or has truly stochastic components? Our study does not answer these questions.

ADDITIONAL REFERENCE

Kiehl, J. T. (2007), "Twentieth Century Climate Model Response and Climate Sensitivity," *Geophysical Research Letters*, 34, *doi:10.1029/2007GL031383*. [468]